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6. AUTHOR(S)
Thomas Huntington Brown

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Yale University, Grant and Contract Administration,
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Attn: Ms Sally Tremaine, Associate Director

8. PERFORMING ORGANIZATION REPORT NUMBER

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11. SUPPLEMENTARY NOTES
Attached letter from Thomas H. Brown dated Sept 16, 1996; attached Report of Inventions form.

12a. DISTRIBUTION/AVAILABILITY STATEMENT
No known restrictions on release of information

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13. ABSTRACT (Maximum 200 words)
We have been working on developing a computationally efficient way to emulate neurons and to emulate circuits and networks of same. We made considerable progress in compressing "realistic" representations of neuronal computations into what we consider functionally equivalent input/output devices, which are now being incorporated into dynamic networks that learn associations and encode time. Our initial hypothesis about how to do this was rejected. Our new hypothesis offers great promise for scaling. This newer hypothesis resulted from examining simulations of "realistic" neurons and thinking about the scaling problem. The latter was funded by the ONR.

14. SUBJECT TERMS
Artificial neural networks; associative learning; Hebbian learning; competitive learning; dynamic processing elements.

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September 16, 1995

Defense Technical Information Center
Building 5, Cameron Station
Alexandria, VA 22304-6145

Re: Final Technial Report on ONR grant N00014-92-192:

Dear Sirs/Mesdames:

This is the final technical report on grant N00014-92-J-1923. This information has also been sent to Dr. Thomas McKenna, the Administrative Grants Officer, and the Director of the Naval Research Laboratory.

The overarching goal of this grant "Neuronal Micronets as Nodal Elements" (N00014-92-J-1923) application was to determine the computational significance of the amount and type of information processing that actually occurs in the nervous system at the single-neuron level.

The basic thesis was that a neuron can be compared to a multi-layered artificial neural network (ANN). The question is, what kind of ANN best captures neuronal computations? This question raises several others: How do neurons differ from the processing elements (PEs) used in connectionistic studies? What do single neurons compute? We have been addressing the latter question through compartmental simulations of hippocampal neurons containing Hebbian synapses.

I used the term "micronet" to refer to the type of ANN that can capture neuronal computations[1]. I concluded that micronets are deep (many layers of PEs) but narrow (relatively few PEs per layer). To function like a neuron, the PEs must operate continuously and asynchronously. There is no clock. Time is its own representation. Connections within a micronet are assumed not to be modifiable, but connections among micronets can exhibit use-dependent modifications, which can be Hebbian. The PE activation function has a passive memory that decays rapidly and exponentially as a function of time.

I requested an AASERT for Sean Murphy, a neuroscience graduate student interested in this problem, but this application was not funded. Murphy went on however, working with another professor in my department, to begin building ANNs that could emulate the input-output functions of neurons, and this grew into part of his dissertation, which was just completed[2]. As I had anticipated, Murphy concluded that an appropriate neural network can indeed emulate a relatively realistic neuronal model in terms of gross input-output functions.

In working with one of my former students, we reached a similar conclusion, based on less formal or extensive analysis. The main difference, however, was that we concluded that, once learning is involved, the circumstance is quite different. And learning was an essential part of the problem we sought to understand. What follows summarizes some of the reasons for rejecting our initial basic thesis that a neuron can be compared to a multilayered ANN. The point is not that the enterprise cannot be done in principle, but that this approach is much too cumbersome relative to certain alternatives, if one is interested in learning.

Part of the reason is that Hebbian learning depends on the electrotonic structure of the cells and this is not easy to capture in connectionist models[3-9]. Hebbian learning depends on the amplitude of the signal at the site of the synaptic input. This in turn means that voltage transfers to and from that site to and from every other synapse must be modeled. In addition, the effects of spiking in the soma must be represented in terms of voltage transfer back through the dendritic tree to the synapses.

These voltage transfers are in general not symmetrical—the attenuation from point i to point j is not the same as from j to i and they are frequency dependent[10]. Furthermore, nonlinear membrane responses, which our modeling suggested to be important[11-13], particularly the backpropagation of action potentials into the dendrites[5], are very difficult to incorporate in an ANN that includes Hebbian learning but have recently been suggested based on experimental data.

Why this insistence on Hebbian learning? Based on first principles, it has always been clear that Hebbian synapses were theoretically important[4,13,14] and we and others had previously shown them to exist in hippocampus. Now it seems that Hebbian synapses are extremely widespread. One sees such synapses in brain regions other than the hippocampus. One even sees such synapses in lower vertebrates. Most recently, it seems that they may even exist in invertebrates.

Thus we continued to explore electrotonic structure in order to understand better how it might interact with active membrane and Hebbian learning[16-20]. At the same time, we developed advanced methods to gain a better understanding of the diversity of cell types and their characteristic active membrane properties[13,21].

My conclusion from this work was that it is computationally easier to use analog models or devices instead of trying to make an ANN emulate what such circuitry would do. If learning can be done off line, or if learning is not involved, then the original idea of representing a neuron as a micronet still makes sense[2]. But from what we now know about the neurophysiology, the nervous system is continuously self-organizing and exhibiting various forms of learning and that these will ultimately depend critically on the electrotonic structure and nonlinear dynamics. Therefore, I focused on the latter. We have gained deep insights into single neuron computations from this enterprise.

We have now begun to formalize the manner in which Hebbian self-organization depends on electrotonic structure[10,22]. The effect of nonlinear membrane probably will differ in different classes of cells and for different types of synaptic inputs. What we are learning is that there is no canonical neuron, even within highly circumscribed brain regions. The number of different types is large and we suspect that this means that brain-style computations require a correspondingly large number of elemental devices—in contrast to the conventional assumptions in ANNs.

You will recall that this application was submitted in March of 1992, and I received notice that it would receive no further funding on August of 1993. At this time I requested a no-cost extension.

We are still publishing work from this period and the enterprise motivated us to collect experimental data that confirmed the conclusions based on the simulations mentioned above. Additional manuscripts are in preparation. I am currently working on what I think may be a fundamental new mechanism for how the nervous system encodes time using Hebbian synapses. I am also continuing to work on the design of a simple device that can, with small quantitative variations, learn and self-organize the way real neurons do. In contrast to Murphy's approach[2], this elemental device would not be an ANN that emulates a particular neuron. Rather I am looking for an analog device that can capture the essence of our insights based on the above considerations. I hope to explore these ideas further through interactions with certain electrical engineers at Yale.

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Sincerely,

Thomas H. Brown, Ph. D
Professor of Psychology
Professor of Cellular and Molecular Physiology

REPORT OF INVENTIONS AND SUBCONTRACTS

(Pursuant to "Patent Rights" Contract Clause) (See Instructions on Reverse Side.)

Form Approved OMB No. 0704-[illegible] Expires Jun 30, 19[illegible]

1a. NAME OF CONTRACTOR/SUBCONTRACTOR: Yale University

c. CONTRACT NUMBER: N00014-92-J-1923

b. ADDRESS (Include ZIP Code): 12 Prospect Place, New Haven, CT 06511

d. AWARD DATE (YYMMDD): 92/07/01

2a. NAME OF GOVERNMENT PRIME CONTRACTOR:

c. CONTRACT NUMBER:

b. ADDRESS (Include ZIP Code):

d. AWARD DATE (YYMMDD):

3. TYPE OF REPORT (X one): a. INTERIM [ ] b. FINAL [X]

4. REPORTING PERIOD (YYMMDD): a. FROM 92/07/01 b. TO 95/06/30

SECTION I – SUBJECT INVENTIONS

5. "SUBJECT INVENTIONS" REQUIRED TO BE REPORTED BY CONTRACTOR/SUBCONTRACTOR (If "None," so state)

a. NAME(S) OF INVENTOR(S) (Last, First, MI)	b. TITLE OF INVENTION(S)	c. DISCLOSURE NO., PATENT APPLICATION SERIAL NO. OR PATENT NO.	d. ELECTION TO FILE PATENT APPLICATIONS (1) United States (a) Yes	(1) United States (b) No	(2) Foreign (a) Yes	(2) Foreign (b) No	e. CONFIRMATORY INSTRUMENT OR ASSIGNMENT FORWARDED TO CONTRACTING OFFICER (1) Yes	(2)
	NONE							

f. EMPLOYER OF INVENTOR(S) NOT EMPLOYED BY CONTRACTOR/SUBCONTRACTOR

(1)(a) Name of Inventor (Last, First, MI)

(b) Name of Employer

(c) Address of Employer (Include ZIP Code)

(2)(a) Name of Inventor (Last, First, MI)

(b) Name of Employer

(c) Address of Employer (Include ZIP Code)

g. ELECTED FOREIGN COUNTRIES IN WHICH A PATENT APPLICATION WILL BE FILED

(1) Title of Invention

(2) Foreign Countries of Patent Application

SECTION II – SUBCONTRACTS (Containing a "Patent Rights" clause)

6. SUBCONTRACTS AWARDED BY CONTRACTOR/SUBCONTRACTOR (If "None," so state)

a. NAME OF SUBCONTRACTOR(S)	b. ADDRESS (Include ZIP Code)	c. SUBCONTRACT NO.(S)	d. DFAR "PATENT RIGHTS" (1) Clause Number	(2) Date (YYMM)	e. DESCRIPTION OF WORK TO BE PERFORMED UNDER SUBCONTRACT(S)	f. SUBCONTRACT DATES (YYMMDD) (1) Award	(2) Estimated Completion
	NONE						

SECTION III – CERTIFICATION

7. CERTIFICATION OF REPORT BY CONTRACTOR/SUBCONTRACTOR (Not required if: [ ] Small Business or [X] Non-profit organization.) (X appropriate box)

a. NAME OF AUTHORIZED CONTRACTOR/SUBCONTRACTOR OFFICIAL (Last, First, MI): Polmar, Suzanne K.

b. TITLE: Director, Grant and Contract Administration

c. I certify that the reporting party has procedures for prompt identification and timely disclosure of "Subject Inventions," that such procedures have been followed and that all "Subject Inventions" have been reported.

d. SIGNATURE: Suzanne K Pol[illegible]

e. DATE SIGNED: 10/24/95

 Previous editions are obsolete.